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Modeling the Symmetric and Asymmetric Volatility for Select Stock Futures in India: Evidence from GARCH Family Models

K Srinivasan*

Abstract

This paper examine the modeling and forecasting volatility of stock futures market in India over the period beginning from 1st April 2003 and ending 31st December 2008, for a total of 1440 observations by using Symmetric GARCH and Asymmetric TGARCH, EGARCH and IGARCH model to draw valid conclusion. In sample analysis is carried out for the period from April 1, 2003 to March 31, 2008 and the remaining 184 observations are used to evaluate the out-of-sample forecasting performance of the model. The forecasting performance of two different models was evaluated by considering two forecasting error statistics like Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). The results of the study indicate that in RMSE statistics, the IGARCH model was performed and it is considered as the best model followed by TGARCH model. Despite its mathematical and statistical simplicity, the IGARCH model provides the most accurate forecast compared to other competing models in the study. Finally, my findings suggest that volatility is a part and parcel of derivative market, which is mainly influenced due to the other key determining factors like inflow of foreign capital into the country like exchange rate, balance of payment, interest rate.

* Faculty of Management Studies, Christ University, Bangalore, Karnataka, India - 560 029; srinivasan@christuniversity.in.

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Introduction

Studies related to price volatility in financial markets have been the focus of academics, policy makers and practitioners over the past decades because it can be used as a measure of risk and often exhibit some well-known characteristics. First, volatility forecasts are sensitive to the specification of the volatility model. In particular, it is important to strike the right balance between capturing the salient features of the data and over fitting the data. Secondly, it is very difficulty to correctly estimate the parameters of a volatility model, because volatility is not observable. Besides, the estimated parameters are the true parameters, which often change the volatility forecasts. Third, volatility forecasts are anchored at noisy proxies or estimates of the current level of volatility. Even with a perfectly specified and estimated volatility model, forecasts of future volatility inherit and potentially even amplify the uncertainty about the current level of volatility.

This study can be considered as one of the few attempts made to examine the most prominent features of time series volatility model for select stock futures contracts, such as volatility clustering, excess kurtosis, and fat tailed etc., to identify which model is the best model according to statistic and risk management evaluation criteria. To capture the above uniqueness, ARCH class of models were introduced by Engle (1982) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) by Bollerslev (1986) and Taylor (1986). Since, the intrinsically symmetric GARCH model does not cope with the asymmetry issues or so called leverage effect, the Exponential Generalized Autoregressive Conditional Heteroskedasticity process (EGARCH) by Nelson (1991) is suggested. Finally, to capture asymmetries in terms of negative and positive shocks TGARCH (Threshold Generalized Autoregressive Conditional Heteroskedasticity) model was introduced by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993). An alternative way to model the intra-day price variation is adopting the price range data instead. The price range is the difference between the daily high and daily low of log-prices, has been used in the academic literature to measure volatility. Financial economists have long known that the daily range of the log price series contains extra information about the course of volatility over the day. Despite the elegant theory and the support of simulation results, the price range as a proxy of volatility has performed poorly in empirical studies. Therefore, the GARCH type of models is most-adopted for modeling the time-varying conditional volatility, because it models the time varying variance as a function of lagged squared residuals and lagged conditional variance.

The rest of the paper is structured as follows. In the next session I, outline some of the previous literature on volatility modeling and forecasting, and the role that news releases play in determining volatility. Section 3 incorporates some of the valuable inputs relating to datasets adopted for the study and methodological issues, while the results and discussion for Symmetric and Asymmetric volatility models are presented in Section 4. Section 5 details the forecasting performance of the estimated models. Here, I begin with Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) error statistics. Section 6 contains my conclusions

Review of Literature

There are numerous investigations on emerging equity markets that outline the different characteristics of emerging equity markets Akgiray (1989), Pagan and Schwert (1990), Bollerslev et.al (1992), Francis and Van Dijk (1996), Brailsford and Faff (1996) and Brooks and Persand (2002). However, many theoretical and empirical studies are designed to work with the conditional variance in developed markets Dimson and Marsh (1990), McMillan, Speight and Gwilym (2000). First, large changes tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility clustering is observed in financial returns data. Secondly, financial time series data often exhibit leptokurtosis, which indicate that return distribution is fat-tailed as observed by Mandelbrot (1963), Fama (1965), Laurent and Peters (2002). Finally, changes in stock prices tend to be negatively related to changes in stock volatility which is identified to be "leverage effect" Black (1976), Christie (1982), Nelson (1991), Koutmas and Saidi (1995). In Sight of the importance of volatility in financial markets, a seminal contribution to the study of stock market volatility was Schwert (1989). He sought to establish which economic variables are highly correlated with volatility in returns, and found little evidence that volatility in economic fundamentals had a discernible influence on stock market returns. Another study by Lamoureux and Lastrapes (1990) assumed that volatility was influenced both by past forecast errors (GARCH) and by the volume of trading, where volume was interpreted as measuring the arrival of new information he conjecture that, in general, GARCH effects in many other studies are really measuring the persistence in the arrival of new information.

Recently, several authors have investigated the volatility of stock market by applying econometric models and suggested that, no single model is superior Akgiray (1989), Pagan and Schwert (1989). Brailsford and Faff (1996) and Koutmos (1998) examine the predictive performance of several statistical methods with GARCH and TGARCH models for Australian stock exchange. The unexpected changes in volatility are the most important risk factor in estimating the cost of portfolio insurance Hill, Jain and wood (1988). Dimson and Marsh (1990) examine various technical methods of predicting the volatility of UK stock market returns and find that exponential smoothening and regression model performed best according to their criteria. Tse (1991), Tse and Tung (1992) examine the stock market of Japan and Singapore respectively, and find that an exponentially weighted moving average method is superior to the GARCH model in both cases. Franses and Van Dijk (1996) compare the volatility forecasting performance of GARCH, QGARCH and TGARCH models to the random walk model using weekly data for Scandinavian stock markets returns over the period 1986 to 1994 and reported random walk model performs particularly well. Brailsford and Faff (1996) compare the predictive performance of several statistical methods with GARCH and TGARCH models using several loss functions, they are unable to identify the superior models and suggest the forecasting models depends upon the sequent application. Harris and Sollis (2003) provide a very good recent overview of the relationship between the variants of various ARCH and GARCH models.

There is a large literature on modeling and forecasting volatility at international level, however only a limited study has appeared in the literature focusing on the Indian stock market. Varma (1999) examine the volatility estimation models comparing GARCH and EWMA models in the risk management setting. Pandey (2002) analyze the extreme value estimators and found the performance with Parkinson estimator for forecasting volatility over these horizons. Karmakar (2005) estimate the movement in stock returns volatility is not explained by the fundamental economic factors, but also the presence of 'fade' due to the actions of noise traders, liberalizing policies and procedures of the government. Kumar (2006) investigate the comparative performance of volatility forecasting models in Indian markets and found that the results are found contrary to Brailsford and Faff (1996). However, further research is needed to forecast the volatility of stock futures market for and an in-depth understanding about the behavioural characteristics of Indian capital markets is needed, to fill the gap in the existing literature.

Data and Methodology

Data Samples

The data for this study consists of observations on the daily closing futures price for 25 stock futures contracts are used for the period beginning on 1st April 2003 and ending 31st December 2008, for a total of 1440 observations and contract trade on the National Stock exchange (NSE) and contract specifications and trading details are available from their website (www. nseindia.com). In sample analysis is carried out for the period from April 1, 2003 to March 31, 2008 (1257 observations) and the remaining 184 observations (from 1st April 2008 to 31st December 2008) are used to evaluate the out-of-sample forecasting performance of the model. Nearby futures contracts are selected for this study, because they are the most actively traded futures contracts within their own classification. The price indices are converted to returns by the standard methods of calculating the log-difference as $R_t = \log (P_t/P_{t-1})$, where P_t represents the value of the index at time t. All the observations are transformed into natural logarithms so that the price changes in futures returns prevents the non-stationarity of the price level series approximate the futures price volatility.

The daily volatility of stock futures returns are estimated by the model developed by Schwert (1990) and Schwert and Seguin (1990). The following equations are†

$$\sigma^2 = \sqrt{\pi / 2} \mid R_t - \mu \mid$$

where, R_t is the return for selected stock futures contracts calculates as described above and μ is mean of the series.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Bollerslev (1986) extended Engle's Autoregressive Conditional Heteroskedasticity (ARCH) model to the GARCH model and it is based on certain assumption that forecasts of time varying variance depend on the lagged variance of the asset. An unexpected increase or decrease in returns at time t will generate an increase in the expected variability in the next period. The basic and most widespread model GARCH can be expressed as;

$$R_t = a + bR_{t-1} + \varepsilon_t \quad \varepsilon_t \mid I_{t-1} \; N(0, h_t),\; h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \alpha_j u_{t-j}^2$$

where, $\alpha_j > 0$, $\beta_i \geq 0$, the GARCH is weekly stationery $\Sigma\beta_i + \Sigma\alpha_j < 1$, the latter two quantifying the persistence of shocks to volatility Nelson (1991). In particular, volatility forecast are increased following a large positive and negative index return, the GARCH specification that capturing the well-documented volatility clustering evident in financial returns data Engle (1982).

Threshold GARCH (TGARCH) Model

In TGARCH model, it has been observed that positive and negative shocks of equal magnitude have a different impact on stock market volatility, which may be attributed to a " leverage effect" Black

† Cao and Tsay (1992) also point out that $\sigma_t = \sqrt{(\pi/2)}|R_t-\mu|$ is an unbiased estimator for the standard deviation

(1976). In the same sense, negative shocks are followed by higher volatility than positive shocks of the same magnitude Engle and Ng (1993). The threshold GARCH model was introduced by the works of Zakoian (1994) and Glosten, Jaganathan and Runkle (1993). The main target of this model is to capture asymmetric in terms of negative and positive shocks and adds multiplicative dummy variable to check whether there is statistically significant different when shocks are negative. The conditional variance for the simple TGARCH model is defined as follows;

$$R_t = a + bR_{t-1} + \varepsilon_t \quad \varepsilon_t \mid I_{t-1} \; N(0, h_t),$$

$$h_t = \omega + \sum_{i=1}^{p} \beta_i u_{t-i}^2 + \sum_{j=1}^{q} \lambda_j h_{t-j} + \delta_i u_{t-1}^2 d_{t-1}$$

where, d_t takes the value of 1 if ε_t is negative, and 0 otherwise. So "good news" and "bad news" have a different impact.

Exponential GARCH (EGARCH) Model

The Exponential GARCH model specifies conditional variance in logarithmic form, which means that there is no need to impose estimation constraints in order to avoid negative variance Nelson (1991). The mean and variance equation for this model is given by;

$$R_t = a + bR_{t-1} + \varepsilon_t \; \varepsilon_t \mid I_{t-1} \; N(0, h_t),$$

$$\log(h_t) = \omega + \sum_{j=1}^{q} \beta_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \lambda_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_i h_{t-1}$$

where, δ captures the asymmetric effect. The exponential nature of EGARCH ensures that the conditional variance is always positive even if the parameter values are negative; thus there is no need for parameter restrictions to impose non-negativity.

Integrated GARCH (IGARCH) Model

The integrated GARCH (p,q) or IGARCH (p,q) model was originally developed by Engle and Bollerslev (1986). In many high-frequency financial time-series data, the conditional variance estimated using a GARCH (1,1) model exhibits a strong persistence. For stationary GARCH models, conditional variance forecasts converge upon the long-term average value of the variance as the prediction horizon increases. For IGARCH processes, this convergence will not happen, while for $\beta_j + \alpha_i > 1$, the conditional variance forecast will tend to infinity as the forecast horizon increases. The mean and variance equation for IGARCH model were as follows;

$$R_t = a + bR_{t-1} + \varepsilon_t \; \varepsilon_t \mid I_{t-1} \; N(0, h_t), \; h_t = \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 = 1$$

where, the estimated parameters of $\beta_j + \alpha_i$ are equal to one, then the IGARCH is a restricted version of the GARCH model. Therefore, there is a unit root in the GARCH process and imply that current information remains of importance when forecasting the volatility for all horizons.

Results and Discussion

In the recent finance literature, the explosion of testing the stationary of the time series data should be kept into consideration for testing the presence of unit root in the variables, otherwise the analyze may produce spurious regression results. The selected stock futures return series was examined for I(1), which is carried out in two steps process in (refer appendix 1). I conducted the unit root test using both the Augmented Dickey Fuller (ADF) test and Phillip-Peron (PP) test, on the first differences for the volatility series. Besides, the unit root test results concludes that stock futures return series are found to be stationary at first-order differencing and integrated at order I(1).

The parameter estimates for typical and parsimonious GARCH (1,1), TAGRCH (1,1), EGARCH (1,1) and IGARCH (1,1) models for the selected stock futures volatility series were examined by using the robust method of Bollerslev-Wooldridge's quasi maximum likelihood estimates assuming with the Gaussian standard normal distribution. F-statistics are used to measure the best fits volatility model for examining the conditional variance of stock futures returns.

The GARCH (1,1) model for futures return series are presented in Table: 2. (refer appendix 2) The lagged return in mean equation was statistically significant for all the stock futures, except CIPLA, INFOSYSTCH and ITC. The conditional variance takes a long time to die out hence the volatility is "persistence", if larger coefficients indicated in GARCH effect. The GARCH coefficient reveals higher for BPCL, GRASIM, HDFC, HINDPETRO, ICICIBANK, SBIN and TATAPOWER, it envisage that new shocks will have the implication on prices for a longer period. In ARCH effect, the large coefficient for BHEL, HCLTECH, ONGC and RANBAXY has more persistence and less reactive in volatility than the other stock futures. The sum of ARCH and GARCH estimates in variance equation is very close to one indicating the volatility shocks are quite persistence, except BHEL, HCLTECH, INFOSYSTCH and RELIANCE. The $\alpha + \beta$ for ACC, BPCL, HCLTECH, HDFC, HINDPETRO, ICICIBANK and TATAPOWER are close to one, which indicate that stock futures returns may be modeled better by a different GARCH models like IGARCH model. Moreover, the higher GARCH effect suggests that recent information is more important than old information and information decays very fast for seven stock futures return series.

To capture the asymmetries in terms of positive and negative shocks TGARCH (1,1) model was envisaged in Table: 3. (refer appendix 3) The ARCH and GARCH effect were remain insignificant for ITC and WIPRO. A positive shock has an impact on $\boldsymbol{\delta_i}$ while the negative shocks have an impact of ARCH (β) + $\boldsymbol{\delta_i}$. If $\delta > 0$, I conclude that there is asymmetry while if $\delta = 0$ the news is symmetric. The result suggest that positive shocks was observed for ONGC and RANBAXY at one per cent level of significant, but the stock futures like HINDPETRO, INFOSYSTCH and ITC identified with insignificant effect. On the other side, the stock futures returns for Dr. REDDY, SBIN and WIPRO were envisaged at five per cent level of significance with negative shocks. The estimated parameter for all the variance envisages that volatility is an asymmetric function of past innovation. Specifically, negative shocks have larger impact on the volatility of the series than positive shocks.

To investigate the leverage effect, I have used EGARCH (1,1) model and their statistical results are given in Table: 4 (refer appendix 4). The lagged returns in mean equation was observed with positive effect and envisaged with one per cent level of significant. The presence of positive asymmetric effect were observed for ACC, BEL, BHEL, BPCL, CIPLA, Dr. REDDY, GRASIM, HCLTECH, HDFC, HEROHONDA, HINDPETRO, ICICIBANK, INFOSYSTCH, M & M, MTNL, NATIONALUM, POLARIS, RELIANCE, SBIN, TATAPOWER and TATATEA with one per cent and five per cent level of significance, which indicate that most of the stock futures was observed with leverage effect. But for ITC, ONGC, RANBAXY and WIPRO the negative asymmetric effect were identified. Moreover, the coefficient of δi term is positive and negative for all estimated parameters with one and five per cent level of significance, which indicates that there exist a leverage effect and asymmetric relationship between the select stock future contracts which indicated that "bad news has larger effects on the volatility of the series than good news". Hence, it can be concluded that the persistence in volatility is very long and explosive and is suggestive of an integrated process.

The parameter estimates of the IGARCH (1,1) model are reported in Table: 5, (refer appendix 5) where in conditional variance, the coefficients of β were found to be significant at 1 per cent level for all the estimates, inferring that the market takes some times to digest the full information into the prices and shocks to conditional variance takes a long time to die out. The a were found to be insignificant for RANBAXY, but for BHEL, Dr. REDDY, HEROHONDA, WIPRO and the stock futures returns were negatively significant at 1 per cent level which indicates less persistence and more reaction in volatility. Hence it can be inferred that the recent information is more important than the old information and the information decays very fast for all the stock futures returns except ITC.

Forecast Evaluation

In order to evaluate the forecasting performance of different models I use two forecasting error statistics by considering the root mean square error (RMSE) and the mean absolute percentage error (MAPE), which are defined as follows:

$$RMSE = \frac{1}{n}\sqrt{\sum_{t=1}^{n}(\sigma_t - \hat{\sigma}_t)^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|(\sigma_t - \hat{\sigma}_t)|/\sigma_t$$

where in all the above statistics *'n'* stand for the number of out of sample forecasts. In this paper I analyze two most popular measures to evaluate the forecasting capability of a model by using RMSE and MAPE. In RMSE the weights of greater forecast errors more heavily in the average forecast error penalty. But, the MAPE denotes the mean of percent deviation to the forecast from the actual series. In short, the model that exhibits the lowest values of the error measurement technique is considered to be the best model.

The results reported in Table: 6 (refer appendix 6) show that the IGARCH model has outperformed all the other models and provides the most accurate forecast in RMSE and MAE respectively. IGARCH model dominates the forecasting performance and it is considered as the best model followed by TGARCH model. On the other hand, the EGARCH model is the worst performing model under both the criteria. Despite its mathematical and statistical simplicity, the IGARCH model provides the most accurate forecast compared to other competing models in the study.

Summary and Conclusion

This paper shed light on the importance of modeling and forecasting stock futures market volatility for various Symmetric and Asymmetric models by using out-of-sample forecast. The dataset covers for the period from April 1, 2003 and ending on December 31, 2008. The forecasting models that are considered here ranges GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and IGARCH (1,1) models. In order to evaluate the forecasting performance of different models I used two forecasting error statistics by considering the root mean square error (RMSE) and the mean absolute percentage error (MAPE) for testing the return characteristics, such as volatility clustering, leptokurtosis and asymmetry effects etc., to identify which model is the best model according to statistic and risk management evaluation criteria. My results suggest that in RMSE statistics, the IGARCH model was performed and it is considered as the best model followed by TGARCH model. Despite its mathematical and statistical simplicity, the IGARCH model provides the most accurate forecast compared to other competing models in the study.

This paper uses several statistical models to estimate and forecast the volatility behavior of stock futures markets. The forecasting models are time varying and complexity in nature, so I investigated according to a wide range of measures and generally mixed results have been recorded. The overall findings of the study have important policy implications to the regulators to the policy makers to strengthen the rules and regulations for the investors in developing countries. First, one cannot conclude that the success or failure of a particular type of forecasting model applied to one market carries over to a different market. Second, the univariate time series model were examined in this study and multivariate models should be kept into consideration to forecast volatility. My findings suggest there are some other variables that are useful to forecast volatility, such as inflation rates, industrial production index or numbers of listed companies is another interesting question to answer. Third, the size and liquidity of a market can affect the quality of volatility forecasts; it is believed that the smaller size of the market would harder to forecast. Fourth, the movement in market return volatility is not only explained by the fundamental economic factors, but also the presence of fade actions taken by noise traders so the market may be associated with these immeasurable elements of price volatility. However, the boost up in share prices and the resultant fluctuation was due to fundamental economic factors of the period which were supplemented by a number of liberalizing policies and procedures of the government. Finally, the real cause of excessive movement was the irrational behaviour of the market where the speculators along with the frenzy investors drove the price away from fundamental level resulting in fade or bubble as the natural outcome of the price formation process.

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Table: 1 Unit Root Test (*appendix 1*)

Sl. No:	Company	ADF Test		PP Test	
		Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
1	ACC	-10.61074	-11.74781	-36.01716	-35.62984
2	BEL	-11.35238	-11.45157	-33.93056	-33.85736
3	BHEL	-14.61881	-15.08222	-36.16696	-35.49959
4	BPCL	-5.590978	-6.184915	-36.84571	-36.27035
5	CIPLA	-16.89831	-16.89236	-37.58669	-37.57509
6	Dr. REDDY	-35.34392	-35.35584	-35.64737	-35.64783
7	GRASIM	-6.219426	-6.328350	-38.94136	-38.81747
8	HCLTECH	-5.694116	-6.007683	-37.66153	-37.20573
9	HDFC	-5.541808	-6.207713	-39.73625	-38.61276
10	HEROHONDA	-8.858530	-8.855722	-34.07336	-34.06591
11	HINDPETRO	-5.171961	-5.534925	-34.98169	-34.48881
12	ICICIBANK	-4.339780	-5.255879	-41.09709	-40.13047
13	INFOSYSTCH	-36.06770	-36.05537	-36.21679	-36.20515
14	ITC	-37.75843	-37.77546	-37.76299	-37.77769
15	M & M	-10.41734	-10.55933	-37.50359	-37.38761
16	MTNL	-6.072162	-6.127391	-32.86795	-32.82077
17	NATIONALUM	-6.347533	-6.713981	-34.64043	-34.14098
18	ONGC	-10.98955	-11.17860	-36.69149	-36.53095
19	POLARIS	-15.59077	-15.78609	-31.27781	-31.16306
20	RANBAXY	-14.63214	-15.27109	-36.16474	-35.68456
21	RELIANCE	-4.976078	-5.999626	-36.92888	-36.17682
22	SBIN	-5.810681	-7.324236	-36.95017	-35.89772
23	TATAPOWER	-7.434996	-7.582331	-33.13445	-32.82715
24	TATATEA	-13.19580	-13.28726	-32.71373	-32.66957
25	WIPRO	-34.44143	-34.45092	-35.21913	-35.20885

Note: The significant value at 1 % for Phillips-Perron test for intercept, trend & with both are – 2.5665, -3.4357 & -3.9667.

Table: 2 Generalized Autoregressive Conditional Heteroskedasticity Model (*appendix* 2)

Note: Figures in the parenthesis report z-Statistics. a & b significance at the 0.01 & 0.05 per cent level respectively.

Sl. No	Company	Coefficients						F – Statistic
		ø	R_{t-1}	ω	α_j	β_i	$\alpha_j + \beta_i$	
1	ACC	0.01[a] (19.73)	0.18[a] (6.84)	4.21E-0[a](7.32)	0.22[a] (9.86)	0.77[a] (36.47)	.993	16.94
2	BEL	0.01[a] (17.00)	0.19[a] (5.19)	0.00[a] (6.52)	0.30[a] (5.10)	0.69[a] (16.66)	.977	20.04
3	BHEL	0.01[a] (29.57)	-0.17[a](-5.71)	0.00[a] (11.27)	0.72[a] (13.06)	0.30[a] (14.92)	1.028	58.49
4	BPCL	0.01[a] (20.14)	0.21[a] (8.09)	6.28E-0[a] (4.14)	0.04[a] (8.64)	0.95[a] (18.03)	.998	13.89
5	CIPLA	0.02[a] (3.07)	-0.00 (-0.10)	0.00[b] (2.11)	0.36[a] (-13.33)	0.59[a] (3.06)	.958	11.38
6	Dr. REDDY	0.01[a] (7.54)	0.16[a] (3.31)	0.00[a] (11.26)	0.23 (1.15)	0.74 (-1.38)	.975	18.13
7	GRASIM	0.01[a] (21.60)	0.17[a] (6.16)	9.15E-0[a] (5.89)	0.10[a] (12.28)	0.89[a] (171.36)	.994	12.28
8	HCLTECH	0.01[a] (16.61)	0.35[a] (9.23)	0.00[a] (13.74)	0.46[a] (29.37)	0.58[a] (26.71)	1.055	60.82
9	HDFC	0.01[a] (21.09)	0.17[a] (5.97)	1.81E-0[a] (4.99)	0.14[a] (10.30)	0.85[a] (65.11)	.995	14.78
10	HEROHONDA	0.01[a] (18.92)	0.22[a] (7.07)	4.32E-0[a] (6.29)	0.13[a] (6.75)	0.74[a] (26.02)	.881	13.64
11	HINDPETRO	0.01[a] (19.66)	0.19[a] (6.26)	2.06E-0[a] (5.86)	0.12[a] (8.90)	0.87[a] (70.08)	.997	18.28
12	ICICIBANK	0.01[a] (19.69)	0.17[a] (5.91)	3.08E-0[a] (6.36)	0.16[a] (9.06)	0.82[a] (47.28)	.993	16.36
13	INFOSYSTCH	0.01b (2.32)	0.15 (0.73)	0.00[a] (13.06)	0.20[a] (3.59)	0.80 (-0.46)	1.010	55.63
14	ITC	0.01 (1.05)	0.00 (0.05)	0.00 (0.765)	0.17 (-0.60)	0.79 (1.13)	.976	28.64
15	M & M	0.01[a] (9.47)	0.21[a] (4.25)	0.00[a] (3.75)	0.26[a] (3.53)	0.67[a] (7.87)	.938	15.53
16	MTNL	0.01[a] (20.47)	0.16[a](4.58)	0.00[a] (8.29)	0.18[a] (11.03)	0.62[a] (20.96)	.804	22.57
17	NATIONALUM	0.01[a] (18.73)	0.29[a] (9.68)	5.220[a] (8.02)	0.19[a] (10.60)	0.79[a] (44.71)	.944	48.37
18	ONGC	0.01[a] (18.22)	0.16[a] (4.68)	0.00[a] (6.81)	0.38[a] (6.38)	0.578[a] (7.04)	.963	13.46
19	POLARIS	0.02[a] (17.37)	0.21[a] (5.58)	0.00[a] (10.55)	0.25[a] (11.27)	0.72[a] (46.46)	.982	32.02
20	RANBAXY	0.02[a] (35.41)	-0.12[a] (-5.34)	0.00[a] (12.64)	0.93[a] (19.14)	0.07[a] (3.93)	1.004	56.78
21	RELIANCE	0.01[a] (23.93)	0.16[a] (4.96)	3.92E-0[a] (7.15)	0.32[a] (33.57)	0.64[a] (36.40)	.964	19.68
22	SBIN	0.01[a] (25.62)	0.16[a] (6.27)	1.28E-0[a] (5.29)	0.07[a] (8.35)	0.89[a] (84.64)	.977	14.91
23	TATAPOWER	0.01[a] (19.84)	0.28[a](9.77)	2.45E-0[a] (6.28)	0.18[a] (12.12)	0.81[a] (55.96)	.997	45.81
24	TATATEA	0.01[a] (19.43)	0.21[a] (6.86)	7.97E-0[a] (7.90)	0.30[a] (7.97)	0.60[a] (15.24)	.908	33.58
25	WIPRO	0.01[a] (5.51)	0.21[a] (2.28)	0.00[a] (14.38)	0.36 (0.92)	0.56 (-0.99)	.927	41.52

Table: 3 Thresholds Generalized Autoregressive Conditional Heteroskedasticity Model(*appendix 3*)

Sl. No:	Company	Coefficients					F – Statistic
		ø	**R_{t-1}**	**β_i**	**δ_i**	**λ_i**	
		0.015[a] (18.117)	0.221[a] (7.564)	0.107[a] (9.045)	-0.286[a] (-5.195)	0.835[a] (41.623)	15.90
2	BEL	0.021[a] (26.901)	0.172[a] (30.822)	0.033[a] (4.856)	-0.581[a] (-7.831)	0.557[a] (11.895)	13.48
3	BHEL	0.020[a] (128.42)	0.097[a] (20.581)	0.914[a] (6.382)	-3.440[a] (-35.46)	0.297[a] (7.990)	15.57
4	BPCL	0.017[a] (19.187)	0.211[a] (7.966)	0.032[a] (8.294)	-0.072[a] (-3.562)	0.955[a] (154.47)	10.85
5	CIPLA	0.035[a] (4.824)	-0.015 (-0.158)	-0.001[a](-113.9)	-0.759[a] (-3.031)	0.596[a] (3.173)	09.49
6	Dr. REDDY	0.015[a] (6.483)	0.263[a] (6.640)	0.005[a] (2.371)	-0.078[b] (-1.933)	0.673 (1.440)	11.55
7	GRASIM	0.015[a] (20.780)	0.172[a] (6.264)	0.088[a] (12.461)	-0.072[a] (-2.277)	0.891[a] (152.92)	10.25
8	HCLTECH	0.027[a] (147.51)	0.114[a] (8.343)	0.044[a] (3.129)	-1.284[a] (-12.787	0.660[a](17.577)	13.76
9	HDFC	0.017[a] (19.923)	0.186[a] (5.661)	0.133[a] (10.071)	-0.252[a] (-4.517)	0.830[a] (50.698)	13.74
10	HEROHONDA	0.015[a] (18.558)	0.195[a] (5.815)	0.156[a] (6.824)	-0.263[a] (-4.542)	0.727[a](23.290)	11.42
11	HINDPETRO	0.017[a] (19.466)	0.193[a] (6.249)	0.094[a] (8.262)	0.007 (0.294)	0.873[a] (66.312)	14.58
12	ICICIBANK	0.018[a] (18.305)	0.191[a] (5.935)	0.118[a] (8.007)	-0.175[a] (-4.025)	0.836[a] (40.147)	14.58
13	INFOSYSTCH	0.018[a] (2.711)	0.232[b] (2.047)	0.043[a] (2.194)	-0.504 (-1.200)	0.563 (1.525)	06.95
14	ITC	0.022 (1.209)	0.005 (0.306)	-0.001 (-0.526)	0.360 (0.177)	0.595 (1.108)	03.45
15	M & M	0.019[a] (16.544)	0.166[a] (6.703)	0.062[a] (9.121)	0.685[a] (7.778)	0.888[a] (74.874)	05.45
16	MTNL	0.019[a] (18.359)	0.179[a] (4.663)	0.239[a] (10.323)	-0.367[a] (-5.641)	0.548[a] (14.063)	20.30
17	NATIONALUM	0.017[a] (15.725)	0.324[a] (9.739)	0.147[a] (9.503)	-0.207[a] (-7.916)	0.808[a] (41.918)	42.03
18	ONGC	0.020[a] (15.950)	0.087[a] (2.325)	0.145[a] (7.710)	0.369[a] (4.671)	0.644[a] (20.027)	07.20
19	POLARIS	0.023[a] (19.422)	0.227[a] (8.178)	0.166[a] (11.274)	-0.549[a] (-8.514)	0.751[a] (45.715)	27.07
20	RANBAXY	0.017[a] (23.041)	0.034[a] (1.975)	0.354[a] (9.583)	6.086[a] (10.648)	0.104[a] (5.871)	24.73
21	RELIANCE	0.015[a] (19.441)	0.211[a] (5.192)	0.393[a] (27.616)	-0.571[a] (-10.96)	0.599[a] (30.463)	22.32
22	SBIN	0.017[a] (24.074)	0.162[a] (5.872)	0.086[a] (8.020)	-0.083[b] (-2.316)	0.888[a] (70.441)	12.55
23	TATAPOWER	0.015[a] (17.584)	0.266[a] (7.642)	0.191[a] (11.673)	-0.271[a] (-6.487)	0.801[a] (51.930)	36.31
24	TATATEA	0.015[a] (16.753)	0.215[a] (5.576)	0.221[a] (6.776)	-0.284[a] (-4.592)	0.590[a] (12.177)	27.58

25	WIPRO	0.022[a] (4.775)	0.181[a] (4.655)	0.003 (0.929)	-0.155[b] (-2.010)	0.593 (1.133)	05.27

Table: 4 Exponential Generalized Autoregressive Conditional Heteroskedasticity Model (*appendix 4*)

Sl. No:	Company	Coefficients					F – Statistic
		ø	R_{t-1}	β_i	λ_i	δ_i	
		0.015[a] (19.10)	0.219[a](7.976)	0.025(0.983)	0.141[a](6.837)	0.900[a](59.034)	15.24
2	BEL	0.019[a](22.041)	0.223[a](6.824)	-0.339[a](-12.17)	0.509[a](17.157)	0.198[a](4.131)	17.31
3	BHEL	0.015[a](22.852)	0.197[a](4.562)	0.349[a](12.050)	0.805[a](39.069)	0.653[a](33.092)	20.09
4	BPCL	0.017[a](20.109)	0.216[a](8.945)	0.066[a](5.411)	0.031[b](2.236)	0.978[a](144.80)	11.23
5	CIPLA	0.024[a](500.75)	-0.009(-1.621)	-1.541[a](-66.42)	1.422[a](128.50)	0.096[a](91.296)	18.79
6	Dr. REDDY	0.010[a](31.231)	0.316[a](17.351)	-1.001[a](-38.42)	1.117[a](35.714)	-0.081[a](-2.510)	21.73
7	GRASIM	0.015[a](21.823)	0.192[a](6.981)	0.160[a](11.079)	0.035[b](2.339)	0.977[a](177.73)	10.52
8	HCLTECH	0.018[a](18.524)	0.340[a](7.044)	0.163[b](2.477)	0.945[a](38.891)	0.445[a](18.829)	16.65
9	HDFC	0.017[a](20.637)	0.186[a](5.807)	0.136[a] (5.801)	0.113[a](4.793)	0.926[a](67.601)	13.91
10	HEROHONDA	0.015[a](18.308)	0.217[a](5.833)	0.105[b](2.392)	0.226[a](6.623)	0.735[a](19.233)	11.56
11	HINDPETRO	0.018[a](18.781)	0.193[a](5.872)	0.164[a](7.618)	0.064[a](3.835)	0.943[a](90.579)	14.63
12	ICICIBANK	0.018[a](21.640)	0.194[a](6.521)	0.125[a](5.169)	0.085[a](4.284)	0.942[a](91.988)	14.31
13	INFOSYSTCH	0.013[a](20.349)	0.449[a](13.39)	-1.005[a](-16.59)	1.187[a](18.705)	0.020(0.663)	21.89
14	ITC	0.019[b](2.328)	0.001(0.272)	0.163(0.447)	-0.766[a](-4.815)	0.029(0.170)	10.24
15	M & M	0.016[a](23.260)	0.232[a](15.68)	-0.652[a](-15.52)	0.801[a](21.096)	-0.082[b](-2.146)	11.95
16	MTNL	0.019[a](18.269)	0.176[a](4.177)	0.217[a](6.290)	0.194[a] (6.036)	0.679[a] (19.477)	20.14
17	NATIONALUM	0.017[a](16.614)	0.321[a](9.945)	0.125[a](6.262)	0.145[a](10.555)	0.895[a](91.967)	41.47
18	ONGC	0.020[a](16.876)	0.123[a](3.693)	0.361[a](20.436)	-0.098[a](-5.160)	0.882[a](45.999)	9.43
19	POLARIS	0.023[a](17.235)	0.231[a](6.025)	0.065[b](2.040)	0.223[a](8.277)	0.828[a](49.025)	27.17
20	RANBAXY	0.016[a](27.874)	0.046[a](3.713)	1.768[a](60.341)	-1.129[a](-29.13)	0.627[a](21.979)	31.45
21	RELIANCE	0.015[a](20.990)	0.196[a](5.401)	0.330[a](10.403)	0.204[a](7.582)	0.840[a](54.552)	20.82
22	SBIN	0.018[a](24.682)	0.158[a](6.036)	0.125a(7.424)	0.081[a](5.939)	0.946[a](105.03)	12.19
23	TATAPOWER	0.016[a](18.366)	0.283[a](8.184)	0.169[a](9.555)	0.153[a](8.420)	0.907[a](90.534)	37.8
24	TATATEA	0.014[a](20.285)	0.258[a](8.694)	-0.003(-0.182)	0.213[a](10.708)	0.864[a](50.591)	29.51

25	WIPRO	0.017[a](25.223)	-0.358[a](-13.45)	3.026[a](18.676)	-1.646[a]-(10.640	0.483[a](25.749)	30.24

Note: Figures in the parenthesis report z-Statistics. * & ** significance at the 0.01 & 0.05 per cent level respectively.

Table: 5 Integrated Generalized Autoregressive Conditional Heteroskedasticity Model(*appendix 5*)

Sl.	Company	Coefficients				
No:		Ø	R_{t-1}	α_i	β_j	F - Statistic
1	ACC	0.015[a] (29.28)	0.239[a] (12.15)	0.024[a] (20.18)	0.975[a] (801.72)	40.62
2	BEL	0.017[a] (22.63)	0.254[a] (17.86)	0.008[a] (10.45)	0.991[a] (122.79)	43.27
3	BHEL	0.031[a](187.02)	0.133[a] (290.60)	-0.005[a] (-309.28)	1.005[a] (541.90)	55.47
4	BPCL	0.017[a] (31.04)	0.215[a] (10.47)	0.028[a] (16.10)	0.971[a] (552.15)	30.38
5	CIPLA	0.060[a] (326.95)	-0.049[a] (-3.72)	0.000[a] (20.10)	0.999[a] (267.80)	36.92
6	Dr. REDDY	0.032[a] (485.33)	-0.129[a] (-21.07)	-0.000[a] (-44.29)	1.000[a] (704.99)	59.61
7	GRASIM	0.015[a] (35.09)	0.189[a] (9.11)	0.06[a] (19.23)	0.933[a] (271.62)	31.23
8	HCLTECH	0.027[a] (11.57)	0.109[a] (4.25)	0.000[a] (33.76)	0.999[a] (666.56)	10.33
9	HDFC	0.017[a] (37.26)	0.176[a] (8.29)	0.085[a] (16.23)	0.915[a] (174.70)	35.98
10	HEROHONDA	0.016[a] (21.43)	0.145[a] (7.61)	-0.001[a] (-4.79)	1.001[a] (280.62)	27.53
11	HINDPETRO	0.018[a] (32.37)	0.222[a] (10.71)	0.060[a] (13.55)	0.939[a] (211.35)	43.87
12	ICICIBANK	0.019[a] (42.78)	0.180[a] (8.94)	0.069[a] (14.57)	0.930[a] (195.45)	40.02
13	INFOSYSTCH	0.021[a] (4.48)	0.034 (0.71)	0.002[a] (61.65)	0.998[a] (306.70)	40.62
14	ITC	0.054[a] (42.50)	1.196[a] (21.22)	0.617[a] (31.60)	0.382[a] (19.60)	43.27
15	M & M	0.038[a] (78.15)	0.052[a] (1.92)	0.108[a] (9.62)	0.891[a] (79.08)	51.53
16	MTNL	0.019[a] (32.65)	0.200[a] (10.25)	0.063[a] (12.17)	0.936[a] (179.55)	87.15
17	NATIONALUM	0.019[a] (37.67)	0.307[a] (15.63)	0.070[a] (17.24)	0.929[a] (226.59)	89.57
18	ONGC	0.026[a] (166.31)	0.098[a] (6.54)	0.003[a] (10.90)	0.996[a](347.10)	54.81
19	POLARIS	0.022[a] (20.91)	0.296[a] (21.32)	0.008[a] (16.61)	0.991[a] (200.07)	109.65
20	RANBAXY	0.040[a] (287.43)	-0.085[a] (-5.57)	0.000 (1.21)	1.000[a] (365.85)	71.82
21	RELIANCE	0.015[a] (39.07)	0.173[a] (7.41)	0.166[a] (55.14)	0.833[a] (275.83)	76.28
22	SBIN	0.017[a] (38.10)	0.184[a] (10.70)	0.047[a] (14.84)	0.953[a] (300.66)	59.87
23	TATAPOWER	0.015[a] (36.16)	0.307[a] (17.54)	0.100[a] (25.42)	0.899[a] (227.01)	48.52

24	TATATEA	0.014[a] (31.04)	0.270[a] (13.89)	0.048[a] (19.48)	0.952[a] (386.00)	36.77
25	WIPRO	0.022[a] (21.93)	0.075[a] (9.77)	-0.001[a] (-22.93)	1.001[a] (145.90)	103.63

Note: Figures in the parenthesis report z-Statistics. * & ** significance at the 0.01 & 0.05 per cent level respectively.

Table: 6 Out of Sample Forecast for Non-Linear Models(*appendix 6*)

Sl. No:		**GARCH**		**TGARCH**		**EGARCH**		**IGARCH**	
	Company	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
1	ACC	.027082	.019227	.026800	.019108	.026876	.019125	.026732	.019066
2	BEL	.027886	.017598	.027519	.018147	.027707	.017818	.027820	.017790
3	BHEL	.039772	.028776	.032436	.023366	.033328	.024416	.029331	.023056
4	BPCL	.030271	.021466	.030307	.021476	.030237	.021459	.030092	.021420
5	CIPLA	.021151	.014939	.024331	.020119	.021143	.015217	.042326	.039471
6	Dr. REDDY	.022925	.014961	.022535	.015021	.023526	.015017	.024279	.018641
7	GRASIM	.030345	.019448	.030309	.019442	.030289	.019474	.030121	.019454
8	HCLTECH	.040759	.029237	.037548	.026902	.038917	.028282	.037651	.026921
9	HDFC	.037556	.027681	.037240	.027478	.037214	.027460	.037141	.027400
10	HEROHONDA	.021416	.015763	.021339	.015729	.021348	.015796	.021228	.015671
11	HINDPETRO	.029453	.020952	.029457	.020953	.029450	.020951	.029197	.020988
12	ICICIBANK	.048006	.033057	.047735	.032967	.047776	.033008	.047458	.032752
13	INFOSYSTCH	.023991	.018765	.023588	.018842	.024507	.019400	.024342	.018720
14	ITC	.021610	.016226	.021180	.016434	.021770	.016201	.066553	.059675
15	M & M	.037056	.023402	.037912	.023562	.037482	.023408	.037897	.027433
16	MTNL	.023187	.016970	.022996	.016946	.023008	.016968	.022846	.016909
17	NATIONALUM	.044709	.029154	.044133	.028905	.044231	.028942	.043804	.028776
18	ONGC	.028129	.019523	.028593	.019519	.028325	.019498	.027594	.020173
19	POLARIS	.044701	.029925	.044507	.029911	.044542	.029935	.044224	.030100
20	RANBAXY	.047870	.028101	.046958	.026961	.047102	.026993	.044531	.029774
21	RELIANCE	.035162	.022259	.034243	.021623	.034472	.021784	.034660	.021912
22	SBIN	.034156	.024084	.034067	.024024	.034108	.024061	.033792	.023792
23	TATAPOWER	.033541	.023408	.033476	.023311	.033405	.023343	.033131	.023326
24	TATATEA	.021079	.014967	.021015	.014972	.021026	.015000	.020889	.015050

25	WIPRO	.032448	.023961	.031859	.023901	.050270	.036842	.033629	.024410

Note: Out of Sample forecast for the period from 1st April 2008 to 31st December 2008 with 184 observations.